Statistical Modeling of the Power Dissipation Index (PDI) and Accumulated Cyclone Energy (ACE)

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ABSTRACT

This study focuses on the statistical modeling of the Power Dissipation Index (PDI) and Accumulated Cyclone Energy (ACE) for the North Atlantic basin over the period 1949-2008, which are metrics routinely used to assess tropical storm activity. To describe the variability exhibited by the data, four different statistical distributions are considered (gamma, Gumbel, lognormal, and Weibull), and tropical Atlantic and tropical mean sea surface temperatures (SSTs) are used as predictors. Model selection, both in terms of significant covariates and their functional relation to the parameters of the statistical distribution, is performed using two different penalty criteria. Two different SST data sets are considered (UK Met Offices HadISSTv1 and NOAAs Extended Reconstructed ERSSTv3b) to examine the sensitivity of the results to the input data.

The statistical models presented in this study are able to describe remarkably well the variability in the observations. Both tropical Atlantic and tropical mean SSTs are significant predictors, independently of the SST input data, penalty criterion, and tropical storm activity metric. The application of these models to centennial reconstructions and seasonal forecasting is illustrated.

1. Introduction

By convolving intensity, duration and frequency, the seasonally integrated Power Dissipation Index (PDI; Emanuel 2005, 2007) and the Accumulated Cyclone Energy (ACE; e.g., Bell et al. 2000; Camargo and Sobel 2005; Bell and Chelliah 2006) are concise metrics used to summarize the activity of a tropical storm season. Both of these measures are computed taking into account the life time of storms and the maximum sustained wind speed. The main difference between PDI and ACE is that the former is computed using the velocities cubed, while the latter the velocities squared. These metrics have been used in different studies examining past tropical storm activity as well as possible changes in climate warming scenarios.

Emanuel (2005) found a strong correlation between the North Atlantic PDI to tropical Atlantic sea surface temperature (SST) (r^2=0.65). Swanson (2008) showed how comparable results could be obtained using relative SST (difference between tropical Atlantic and tropical mean SSTs). Vecchi et al. (2008) explores the implications of Swanson (2008) for attribution of past and projections of future PDI changes, and also showed how describing PDI as a linear function of relative SST would provide a better agreement with dynamical modeling results than using tropical Atlantic SST for climate change scenarios. Klotzbach (2006) found a significant increasing linear trend in North Atlantic ACE over the period 1986-2005 (see also Wu et al. (2008)), and a statistically significant correlation between North Atlantic SST and ACE.

In studies examining the relation between these indexes and climate-related predictors, linear regression is generally used after transforming the data to account for their skewness (e.g., Saunders and Lea 2005; Vecchi et al. 2008). Mestre and Hallegatte (2009) focused on the statistical modeling of the largest PDI each year. Despite their wide use, detailed statistical modeling of the PDI and ACE indexes is still lacking. In particular, outstanding questions revolve around the statistical distribution of these metrics, as well as the dependence of the parameters of this distribution on climate-related indices. An improved understanding of the physical mechanisms controlling PDI and ACE could provide a foundation for improved capability of seasonal forecast of tropical storm activity and better insight into possible interannual to centennial changes in tropical storm activity in response to climate variability and change. The topic of this study is, therefore, the statistical modeling of these two metrics in terms of climate indexes.

2. Generalized Additive Model in Location, Scale and Shape (GAMLSS)

Statistical modeling of the PDI and ACE over the period 1949-2008 for the North Atlantic basin is performed using the Generalized Additive Model in Location, Scale, and Shape (GAMLSS), proposed and developed by Rigby and Stasinopoulos (2005). The advantage of the GAMLSS with respect to other models, such as Generalized Linear Model, Generalized Additive Model, Generalized Linear Mixed Model, is that we are not restricted in using distributions from the exponential family (e.g., Gaussian, exponential) but we can fit using a distribution from a more general set of distribution functions (e.g. highly skewed and/or kurtortic continuous and discrete distributions). This statistical framework was already successfully used to describe other hydrometeorological variables (Villarini et al. 2009a, 2009b, 2010a). Because these two metrics are continuous and can only have positive values, we explore these four two-parameter distributions: gamma, Gumbel, lognormal, and Weibull. We model the parameters of these distributions as a linear or nonlinear (via cubic splines) function of covariates. Following Swanson (2008) and Vecchi et al. (2008), we focus on tropical Atlantic (SST_{Atl}) and mean tropical (SST_{trop}) SSTs as possible covariates. Two different input data sets are considered: UK Met Offices HadISSTv1 (Rayner et al. 2003) and NOAAs Extended Reconstructed SST (ERSSTv3b; Smith et al. 2008), and averaged over the period June-November. The use of two data sets provides information about the sensitivity of our results to uncertainties in SST reconstructions. The tropical Atlantic SST anomalies (SST_{Atl}) are computed for over 10N-25N and 80W-20W, while the mean tropical SST (SST_{Trop}) over the global tropics (30S-30N).

Model selection, both in terms of predictors and their functional relation to the parameters of these distributions, is performed using a stepwise method penalizing with respect to both the Akaike Information Criterion (AIC; Akaike 1974) and the Schwarz Bayesian Criterion (SBC; Schwarz 1978). Quality of the fit is assessed by comparing the first four statistical moments of (normalized quantile) residuals against a standard normal distribution, together with their Filliben correlation coefficient (Filliben 1975), and by visual examination of the residuals' plots (e.g., qq-plot, worm plot; van Buuren and Fredriks 2001; Stasinopoulos and Rigby 2007). For a comprehensive discussion about the GAMLSS, the reader is pointed to Rigby and Stasinopoulos (2005) and Stasinopoulos and Rigby (2007). All the calculations are performed in `R` (R Development Core Team 2008) using the freely available `gamlss` package (Stasinopoulos et al. 2007).

3. Results

Modeling of the PDI and ACE in terms of tropical Atlantic and tropical mean SSTs is performed using the GAMLSS. Focusing first on PDI, Figure 1 shows the results obtained using AIC as penalty criterion (see Figure S1 for results using SBC). Summary of the models' fit is presented in Table 1. Independently of the penalty criterion and SST input data, both tropical Atlantic and tropical mean SSTs are always retained by the model as significant predictors (see also Villarini et al. (2010b)). Moreover, the former has a positive coefficient, while the latter a negative one. This is in agreement with the results in Swanson (2008) and Vecchi et al. (2008). The magnitude of these coefficients is larger for tropical Atlantic, suggesting that uniform SST warming should lead to tropical storm seasons with larger PDI. The ratio of the coefficients linking SST_{TROP} and SST_{MDR} to the mean is between 0.77-0.85, in close agreement with the linear regression results of Swanson (2008). These models describe very well the variability exhibited by the data, with alternating periods of increased and decreased activity. The model fit diagnostics (Figures 1 and S1, right panels; Table 1) support the choice of these models. When using ERSSTv3b data for modeling PDI, independently of the penalty criterion the gamma distribution with the logarithm of the μ parameter linear function of both tropical Atlantic and tropical mean SSTs is selected as final model. The picture is slightly different when using HadISSTv1 data. The Weibull distribution with $\log(\mu)$ depending on both of the predictors by means of a cubic spline is selected when penalizing with respect to AIC. On the other hand, a gamma distribution with $\log(\mu)$ depending linearly on both predictors is selected when penalizing with respect to SBC.

The results and conclusions for the ACE are similar to what found for the PDI (Figures 2 and S2; Table 2). Both tropical Atlantic and tropical mean SSTs are included in the final models, with the coefficient of the former (latter) having a positive (negative) sign (see also Villarini et al. (2010b)). The results using ERSSTv3b data are the same independently of the penalty criterion, with the gamma distribution being the selected distribution with the $\log(\mu)$ depending linearly on both predictors. The results for the HadISSTv1 data, both in terms of parametric distribution and functional relation of its parameters on the covariates, depend on the penalty criterion. When using AIC, the data can be described by a Weibull distribution with the μ parameter depending on the SST predictors by means of a cubic spline (via a logarithmic link function). The gamma distribution with $\log(\mu)$ depending linearly on both predictors is selected when penalizing with respect to SBC. These models are able to describe remarkably well the variability exhibited by the data, as also supported by the fit diagnostics (Figures 2 and S2, right panels; Table 2). Differently from the PDI results, the values of the coefficients of the two predictors have similar magnitude and opposite sign, suggesting that a uniform increase in SST would lead to little change in seasonal ACE, with the remote warming offsetting the Atlantic warming.

4. Discussion and Conclusions

In this study we have focused on the Power Dissipation Index (PDI) and Accumulated Cyclone Energy (ACE) for North Atlantic tropical storms over the period 1949-2008. We have examined the dependence of these two metrics on tropical Atlantic and tropical mean SSTs. Statistical modeling was performed using the GAMLSS. Two different penalty criteria (AIC and SBC) were selected, as well as two different SST input data sets (ERSSTv3b and HadISSTv1).

Our results indicate that both tropical Atlantic and tropical mean SSTs are significant covariates in describing the variability of PDI and ACE for North Atlantic tropical storms, providing additional evidence to the importance of relative SST on the tropical storm activity. For both PDI and ACE, the coefficient of tropical Atlantic SST had a positive sign, while the coefficient for tropical mean SST was negative. For PDI the coefficient for the Atlantic SST was larger than for the tropical SST, suggesting that a uniform increase in SST in a warmer climate would result in an increase in PDI. For the ACE the magnitude of the two coefficients were much more similar, not suggesting an increase in ACE values under uniform SST warming. Because PDI depends on the wind speed to the third power, while ACE to the second power, an interpretation of the differences in the relative amplitudes of the SST_{Atl} and SST_{trop} coefficients of the models for PDI and ACE is that the response of intensity of the most intense storms and overall tropical storm frequency to uniform warming is different. This is in qualitative agreement with the dynamical modeling results indicating that the intensity and frequency response of Atlantic tropical cyclones to global warming can differ (Emanuel et al. 2008, Knutson et al. 2008, Bender et al. 2010, and Zhao and Held 2010).

The statistical models provide a framework with which to reconstruct the PDI and ACE time series prior to 1949 using reconstructed SST time series (e.g., Figure 3, top panel). These reconstructions could provide information about the North Atlantic tropical storm activity in the past, placing recent variations on a larger context. The centennial reconstruction of PDI indicates periods of enhanced and reduced variability over the past 130 years on a variety of time scales. Thus, the PDI reconstruction indicates that there have been periods before 1949 that were comparably active to the post-1995 era of heightened activity. Future work will explore modifying the methodology of Mann et al. (2009) using these models to build multi-centennial reconstructions of PDI and ACE.

Apart from information about possible changes in tropical storm activity from decadal to centennial climate variations and change, another application of our models is related to the seasonal forecast of PDI and ACE (e.g., Camargo et al. 2007; Klotzbach 2007; Klotzbach and Gray 2009; Vecchi et al. 2011). For instance, the NOAA Climate Prediction Center (CPC) uses the ACE value to classify a North Atlantic tropical storm season into above-, near-, and below-normal. Recently, Vecchi et al. (2011) proposed a hybrid statistical-dynamical model that can be used to forecast hurricane counts starting from September of the previous year. As an example, we have "forecasted" the PDI distribution using a 10-member June-November tropical Atlantic and tropical mean SST forecasts initialized in January. The correlation coefficient between observations and the median of the PDI distribution over the period 1982-2009 is 0.77, with a RMSE of 1.51×10^{11} m^3s^{-2} and a MAE of 1.11×10^{11} m^3s^{-2} (Figure 3, bottom panel). Even though we have forecasted the period used for model fitting, results obtained from leave-one-out cross validation support the predictive capability of this model (compared to the full model, the correlation coefficient is 0.51 versus 0.58, the RMSE is 1.39×10^{11} m^3s^{-2} versus 1.32×10^{11} m^3s^{-2}, and the MAE of 1.03×10^{11} m^3s^{-2} versus 0.98×10^{11} m^3s^{-2}; these results are for the period 1949-2008). These preliminary results are encouraging, and in a future study we will examine the applicability of our statistical models to the seasonal forecast of PDI and ACE, in a fashion similar to what described in Vecchi et al. (2011).

One element that requires further discussion is the fact that tropical Atlantic and tropical mean SSTs are correlated (the correlation between these two predictors is equal to 0.73 for HadISSTv1 and 0.78 for ERSSTv3b). At the onset, it is worth clarifying that, even though these values may appear large, they are not nearly as large as those in studies from other disciplines (e.g., Burnham and Anderson 2004; Stasinopoulos and Rigby 2007). As a rule of thumb, Burnham and Anderson (2002) suggested to keep all the predictors unless the correlation coefficient is extremely high, with |0.95| as a cutoff value for dropping a covariate. To assess whether collinearity may have affected our results, we use the variance inflation factor (VIF). This is a diagnostic tool commonly used to evaluate the impact of collinearity, by quantifying the impact of the correlation among predictors on inflating the sampling variance of an estimated regression coefficient. For the gamma models, we compute the VIF using the `vif` function in the `Design` package (Harrell Jr 2009) in `R` (R Development Core Team 2008), in which the method described in Davis et al. (1986) is implemented (see also Wax (1992)). A VIF value of 10 is generally used to decide whether collinearity is high (e.g., Davis et al. 1986, O'Brien 2007) and this is the cutoff value we use. Independently of the SST input data and tropical storm activity metric, the VIF values are smaller than 3, indicating that the impact of collinearity does not significantly affect the results of this study (see also discussion in Villarini et al. (2011)).

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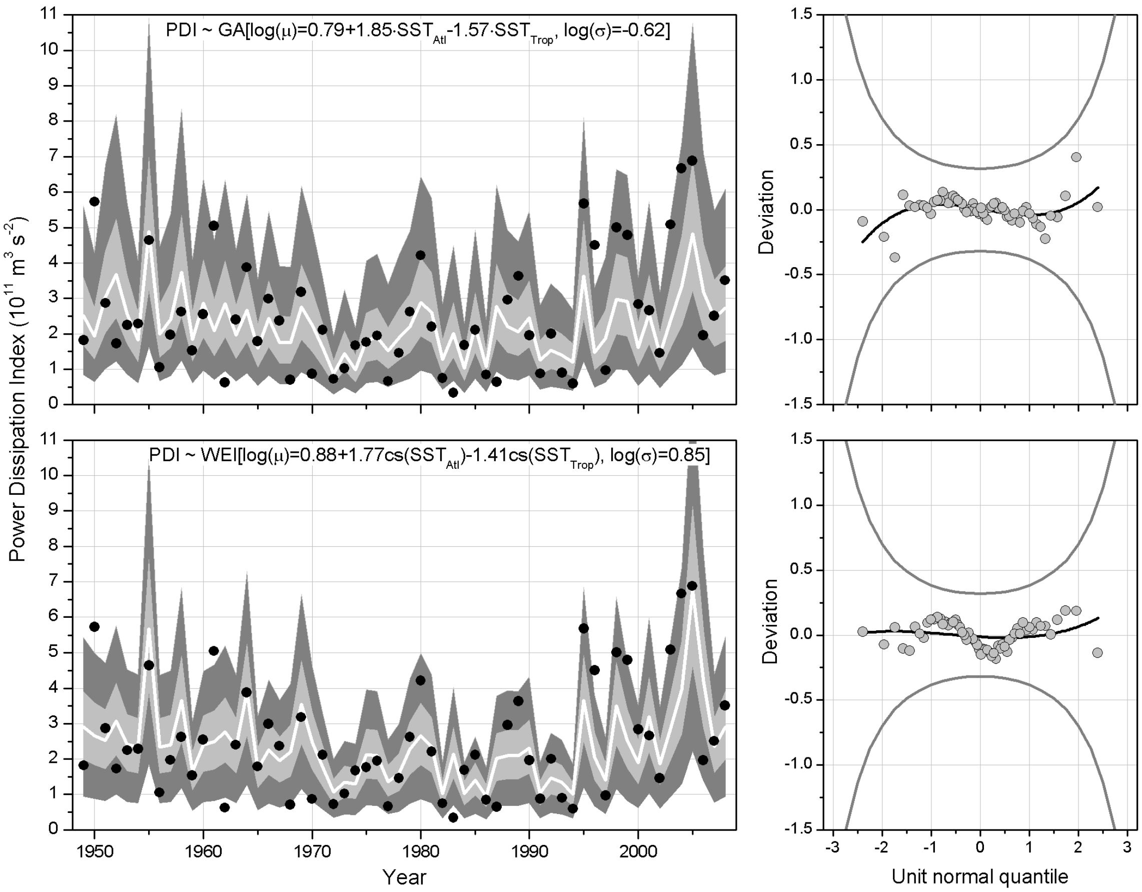
FIG. 1. Left panels: Modeling of the Power Dissipation Index (PDI) with a gamma distribution (top panel) and Weibull distribution (bottom panel) with parameters depending on tropical Atlantic and tropical mean SSTs. The results in the top panel are based on the ERSSTv3b data, while those on the bottom on the HadISST data. Model selection is performed with respect to AIC. The dots are observations; the white line represents the 50^{th} percentile, the light grey area the region between the 25^{th} and 75^{th} percentiles, and the dark grey area the region between the 5^{th} and 95^{th} percentiles. In the top panel, “GA” stands for gamma distribution; in the bottom panel, “cs” stands for cubic spline and “WEI” for Weibull distribution. Right panels: Worm plots used to assess the quality of the fit.

FIG. 2. Left panels: Modeling of the Accumulated Cyclone Energy (ACE) with a gamma distribution (top panel) and Weibull distribution (bottom panel) with parameters depending on tropical Atlantic and tropical mean SSTs. The results in the top panel are based on the ERSSTv3b data, while those on the bottom on the HadISST data. Model selection is performed with respect to AIC. The dots are observations; the white line represents the 50^{th} percentile, the light grey area the region between the 25^{th} and 75^{th} percentiles, and the dark grey area the region between the 5^{th} and 95^{th} percentiles. In the top panel, “GA” stands for gamma distribution; in the bottom panel, “cs” stands for cubic spline and “WEI” for Weibull distribution. Right panels: Worm plots used to assess the quality of the fit.

FIG. 3. Top panel: Reconstruction of the PDI from 1878 using the gamma model obtained from the ERSSTv3b data. Bottom panel: Forecast of PDI over the period 1949-2010 using a 10-member June-November SST forecast initialized in January. In both of the panels, the dots are observations; the white line represents the 50^{th} percentile, the light grey area the region between the 25^{th} and 75^{th} percentiles, and the dark grey area the region between the 5^{th} and 95^{th} percentiles. The solid black line in the top panel represents the 5-year running mean of the median.



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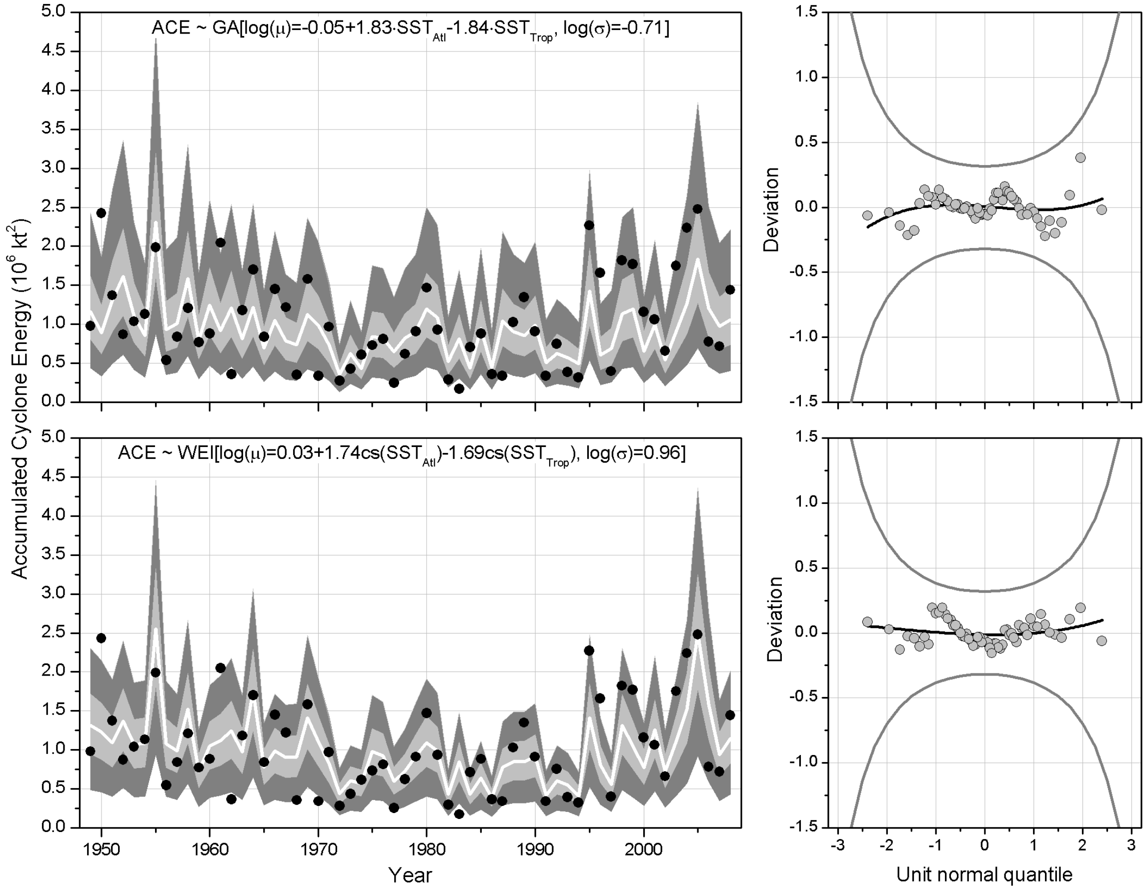

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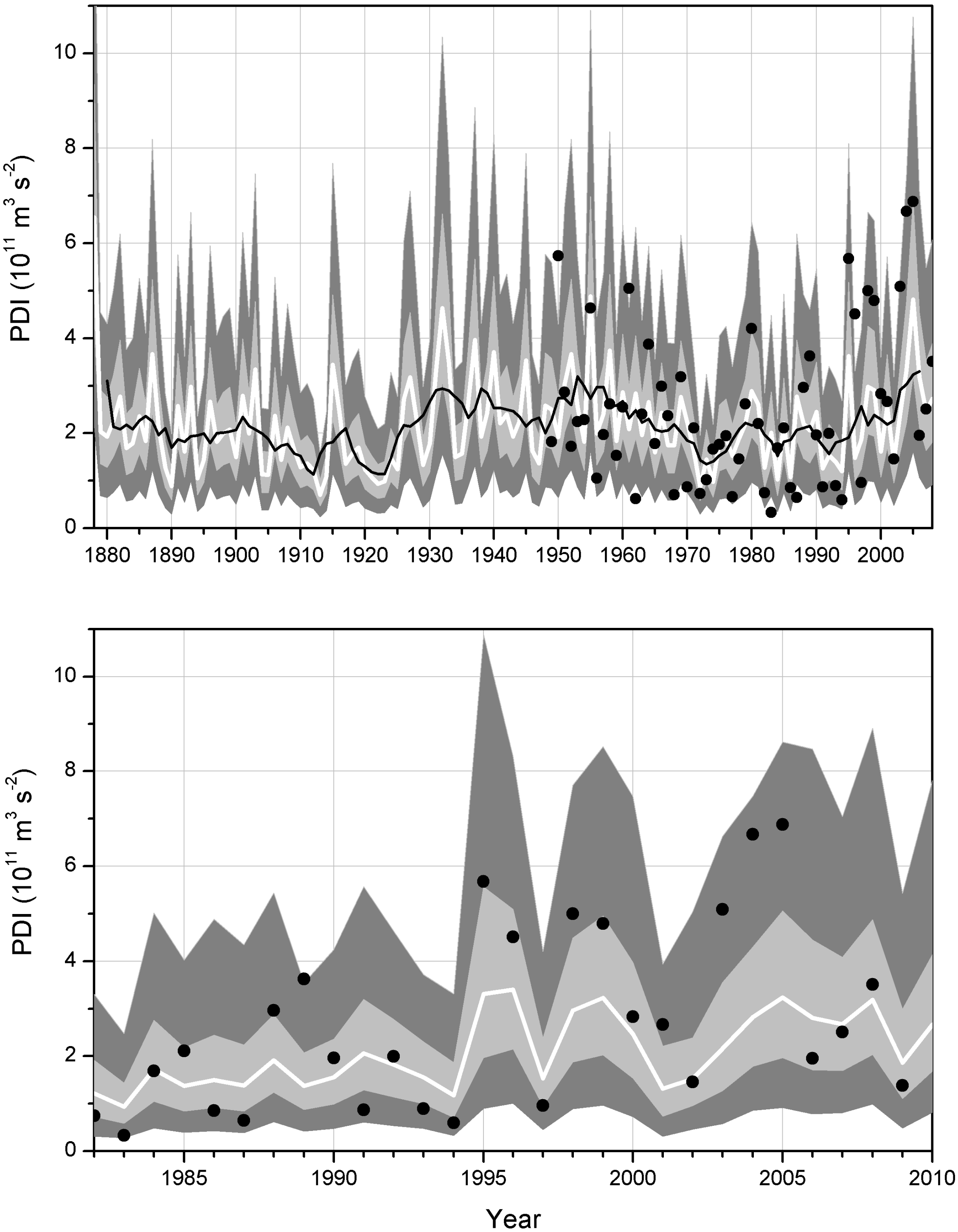

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TABLE 1. Summary statistics for the modeling of the Power Dissipation Index (PDI) using tropical Atlantic and tropical mean SSTs as covariate. The first value is the point estimate, while the one in parentheses is the standard error. In each cell, the values in the first (second) row refer to the model selected with respect to AIC (SBC). When ‘‘cs’’ is present, it means that the dependence of the parameters on that covariate is by means of a cubic spline (otherwise, linear dependence is implied).

PDI	ERSSTv3b	HadISSTv1
Distribution	Gamma Gamma	Weibull Gamma
Intercept	0.79 (0.09) 0.79 (0.09)	0.88(0.08) 0.78 (0.08)
$\log(\mu)$:SST_{Atl}	1.85 (0.35) 1.85 (0.35)	1.77 (0.32; cs) 1.78 (0.32)
$\log(\mu)$:SST_{trop}	-1.57 (0.48) -1.57 (0.48)	-1.41 (0.46; cs) -1.37 (0.46)
$\log(\sigma)$	-0.62 (0.09) -0.62 (0.09)	0.85 (0.10) -0.63 (0.09)
Mean (residuals)	0.00 0.00	0.00 0.00
Variance (residuals)	1.02 1.02	1.00 1.02
Skewness (residuals)	-0.04 -0.04	0.08 -0.16
Kurtosis (residuals)	3.12 3.12	2.79 2.83
Filliben (residuals)	0.995 0.995	0.995 0.995
AIC	192.9 192.9	189.6 191.4
SBC	201.3 201.3	210.5 199.8

TABLE 2. Same as Table 1 but for the Accumulated Cyclone Energy (ACE).

ACE	ERSSTv3b	HadISSTv1
Distribution	Gamma Gamma	Weibull Gamma
Intercept	-0.05 (0.08) -0.05 (0.08)	0.03 (0.08) -0.07 (0.07)
log(μ):SST$_{Atl}$	1.83 (0.33) 1.83 (0.33)	1.74 (0.29; cs) 1.78 (0.29)
log(μ):SST$_{trop}$	-1.84 (0.43) -1.84 (0.43)	-1.59 (0.41; cs) -1.66 (0.41)
log(σ)	-0.71 (0.09) -0.71 (0.09)	0.96 (0.10) -0.73 (0.09)
Mean (residuals)	0.00 0.00	0.00 0.00
Variance (residuals)	1.02 1.02	1.01 1.02
Skewness (residuals)	-0.03 -0.03	0.08 -0.18
Kurtosis (residuals)	2.90 2.90	2.72 2.78
Filliben (residuals)	0.995 0.995	0.996 0.995
AIC	77.8 77.8	72.8 74.4
SBC	86.1 86.1	93.7 82.7